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Annual high-resolution grazing intensity maps on the Qinghai-Tibet Plateau from 1990 to 2020

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Abstract. Grazing activities constitute the paramount challenge to grassland conservation over the Qinghai-Tibet Plateau (QTP), underscoring the urgency for obtaining detailed extent, patterns, and trends of grazing information to access efficient grassland management and sustainable development. Here, to inform these issues, we provided the first annual Gridded Dataset of Grazing Intensity maps (GDGI) with a resolution of 100 meters from 1990 to 2020 for the QTP. Five most commonly used machine learning algorithms were leveraged to develop livestock spatialization model, which spatially disaggregate the livestock census data at the county level into a detailed 100 m× 100 m grid, based on seven key predictors from terrain, climate, land cover and socioeconomic factors. Among these algorithms, the extreme trees (ET) model performed the best in representing the complex nonlinear relationship between various environmental factors and livestock intensity, with an average absolute error of just 0.081 SU/hm^2, a rate outperforming the other models by 21.58%~414.60%. By using the ET model, we further generated the GDGI dataset for the QTP to reveal the spatio-temporal heterogeneity and variation in grazing intensities. The GDGI indicates grazing intensity decreased from 1990 to 2001 period, and fluctuated thereafter. Encouragingly, comparing with other open-access datasets for grazing distribution on the QTP, the GDGI has the highest accuracy, with the determinant coefficient (R^2) exceed 0.8. Given its high resolution, recentness and robustness, we believe that the GDGI can significantly enhance understanding of the substantial threats to grasslands emanating from overgrazing activities. Furthermore, the GDGI product holds considerable potential as a foundational source for research, facilitating rational utilization of grasslands, refined environmental impact assessments, and the sustainable development of animal husbandry. The GDGI product developed in this study is available at https://figshare.com/s/ad2bbc7117a56d4fd88d (Zhou et al., 2023).

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1 Introduction

Livestock is a crucial contributor to global food systems through the provision of essential animal proteins and fats, and plays a significant role in supporting human survival and socio-economic development (Gilbert et al., 2018; Godfray et al., 2018; Humpenöder et al., 2022; Kumar et al., 2022). However, the escalating increase in human demand for meat and dairy products over recent decades has triggered a livestock boom, which in turn has increasingly threatened grassland ecosystems and placed a heavy burden on the environment through overgrazing and land-use change (Tabassum et al. 2016, Wei et al. 2022, Minoofar et al. 2023). It is estimated that up to 300 million hectares of land are used globally for grazing and cultivating fodder crops (Tabassum et al. 2016). Grazing activities could alter vegetation phenology and community structure (Dong et al., 2020), and trigger deforestation (García-Ruiz et al., 2020), grassland degradation (Sun et al., 2020), soil erosion (Shakoor et al., 2021), and associated direct releases in greenhouse gas that lead to climate change feedback (Godfray et al., 2018; Chang et al., 2021). Additionally, livestock are responsible for large-scale dispersion of pathogens, organic matter, and residual medications into soil and groundwater, thereby contaminating the environment (Tabassum et al., 2016; Hu et al., 2017; Muloi et al., 2022). Consequently, more and more scholars have called attention to provide reliable contemporary dataset to illustrate the spatio-temporal heterogeneity and variation of livestock (Fetzel et al., 2017; Zhang et al., 2018; Li et al., 2021).

One of the major challenges in monitoring grazing activity at regional or even larger scale, is the determination of the livestock distribution pattern. Despite the importance of geographical grazing information, high spatio-temproal grazing dataset remain unavailable, posing the most critical challenge to grassland management, particularly for vulnerable grassland ecosystems in fragile regions grappling with economic and sustainable development contradictions (Miao et al., 2020; Pozo et al., 2021; He et al., 2022; Meng et al., 2023). In the early 2000s, the Food and Agriculture Organization of the United Nations (FAO) launched the Gridded Livestock of the World (GLW) project to facilitate a detailed evaluation of livestock production, aiming to provide pixel-scale livestock densities instead of traditional administrative unit benchmarks (Nicolas et al., 2016). Consequently, the world's inaugural dataset of livestock spatialization map (GLW1) was released in 2007, providing the first globally standardized livestock density distribution map at a spatial resolution of 0.05 decimal degrees (≈5 km at the equator) for 2002. It was not until 2014 that an updated GLW2 map with a 1 km resolution for 2006 was released, by using a stratified regression approach, superior spatial resolution predictor variables, and more detailed livestock census data (Robinson et al., 2014). Furthermore, an evolutionary step in machine learning technology saw Gilbert et al. (2018) using random forest algorithms to forge a global livestock distribution map with a 10-km resolution for 2010 (GLW3), succeeding traditional multivariate regression methods and surpassing the precision of previous GLW1 and GLW2 maps. Beyond these global mappings, several maps with different scales have also been published, including intercontinental, national, state or provincial, and local scale (Prosser et al., 2011; Van Boeckel et al., 2011; Nicolas et al., 2016). However, these maps are fundamentally coarse due to constraints such as the availability of fine scale and contemporary census data, the grazing spatialization method, as well as the identification of appropriate indicators, thereby limiting their application to local or regional-scale studies (Robinson et al., 2014; Nicolas et al., 2016; Gilbert et al., 2018). Hence, there is an emergent demand for more refined grazing map products (Mulligan et al., 2020; Martinuzzi et al., 2021).

An exemplar of this need can be observed in the Qinghai-Tibet Plateau (QTP), the world's most elevated pastoral region and an important grazing area in China (Zhan et al., 2023). It was possessing

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abundant grassland that spans 1.5 million km^2, accounting for 50.43% of China's total grassland area, with Yak and Tibetan sheep as primary grazing livestock (Cai et al., 2014; Zhan et al., 2023). Over recent decades, the QTP has undergone escalating grassland degradation, leading to many ecological and socio-economic problems, which calls for an urgent need for detailed livestock distribution dataset (Li et al., 2022a). Unfortunately, despite researchers' efforts at mapping the QTP's grazing intensity, current livestock dataset still suffer from coarse spatio-temporal resolution and modelling accuracy. Apart from the aforementioned global grazing dataset, several other maps also cover the QTP. For instance, Liu et al. (2021) generated an annual 250-m gridded carrying capacity map for 2000-2019 employing multiple linear regressions of livestock numbers, population density, NPP, and topographic features. Li et al. (2021) used machine learning algorithms to produce gridded livestock distribution data at 1 km resolution for 2000-2015 in western China at five year interval, based on county-level livestock census and 13 factors including NDVI, topography, climate, and population density (Li et al., 2021). A contribution from Meng et al. (2023) brought forth annual longer time-series grazing maps using a random forest model, integrating climate, soil, NDVI, water distance, and settlement density to decompose county-level livestock census data to a 0.083° (≈10 km at the equator) grid for 1982-2015 (Meng et al., 2023). Similarly, Zhan et al. (2023) also used a random forest algorithm to combine eleven influence factors to provide a winter and summer grazing density map at a 500 m resolution for 2020.

However, although these maps have provided good help in understanding grazing conditions on the QTP, there are currently still no maps that can satisfy the need for fine-scale grassland management with a long time span. In addition, the available livestock distribution maps of the QTP still need improvement in terms of modelling techniques and factor selection to obtain high-precision livestock spatialization data. For example, traditional methods like multilayer linear regression, while proven fundamental and widely applicable for livestock spatialization (Robinson et al., 2014; Ma et al., 2022), are being challenged by the development of computational science in recent years. Among them, machine learning technology is providing new opportunities towards more accurate predictions of livestock intensity (García et al., 2020). Random forest regression, for instance, is currently widely used to construct global, national as well as regional livestock spatialization dataset, and has been proved to have much better accuracy than traditional mapping techniques (Rokach, 2016; Nicolas et al., 2016; Gilbert et al., 2018; Chen et al., 2019; Dara et al., 2020; Li et al., 2021). Nevertheless, other more advanced machine learning methods with superior feature learning and more robust generalization capabilities, remains largely untapped for modelling geographic data (Ahmad et al., 2018; Heddam et al., 2020; Long et al., 2022). Thus, exploring the potential application of new advanced machine learning technologies in livestock spatialization remains a critical task. Furthermore, selecting the suitable factors that influencing livestock grazing preferences is also the other critical challenge for enhancing the precision of grazing dataset (Meng et al., 2023). Livestock grazing activities are often affected by abiotic and biotic resources, including climatic and environmental factors (Waha et al., 2018), herd foraging and grazing behaviours (Garrett et al., 2018; Miao et al., 2020), and conservation-oriented policies (Li et al., 2021). For instance, regions exceeding elevations of 5600 m or slope greater than 40% are customarily unsuitable for grazing (Mack et al., 2013; Robinson et al., 2014; Chen et al., 2019). The livestock generally prefer areas abundant in water and pasture resources for foraging (Li et al., 2021). Besides, ecological conservation policies also exert substantial influence, significantly affecting grazing distribution relative to the level of conservation priority. In addition, the health status of the grassland is an important factor influencing whether livestock choose to feed or not (Li et al., 2021). Consequently, indicators related to the above aspects are often employed to gauge the spatial heterogeneity of livestock

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distribution (Allred et al., 2013; Sun et al., 2021; Meng et al., 2023). Nonetheless, some most commonly used indicators like NPP or NDVI can result in misconceptions, as they may not fully characterize the grazing intensity. For example, grasslands with high NPP or NDVI are often preferred by livestock, but this doesn't necessarily correlate with grazing intensity in nature reserves due to strict policy restrictions (Veldhuis et al., 2019; Zhang et al., 2021b). Conversely, areas with sparse grassland cover may support considerable livestock numbers, despite evidence of degradation (Guo et al., 2015; Zhang et al., 2021a). Accordingly, further investigation of novel indicators is imperative to enhance the correlation between grassland and grazing intensity, thereby optimizing the integration of such influencing factors into grazing spatialization models.

In summary, the QTP is in pressing need for a high spatio-temporal resolution grazing dataset to address urgent and realistic challenges. But the existing livestock dataset specific to the QTP are fraught with several insufficient, predominantly concerning rough resolution, relatively backward census data, and conventional methods in livestock spatialization. Moreover, the discrepancies in predictive indicators and modelling approaches within these dataset discourage their application in time-series analysis. Consequently, the generation of high-resolution and high-quality grazing map products has emerged as the most pressing challenge for the QTP. Here, we aim to (1) establish a new methodological framework to improve the traditional methods in generating gridded grazing dataset; (2) select the grazing spatialization model with good performance by incorporating multi-source data with advanced machine learning techniques; and (3) ultimately, provide an annual grazing intensity map with 100 m resolution spanning from 1990-2020. These maps can not only provide fundamental comprehensive dataset with finer spatio-temporal resolution to improve degraded grassland and enhance sustainability through stocking rates adjustment across the QTP, but support a better understanding of other socio-economics related studies.

2 Data and methods

2.1 Study area

Known as the Asia's water tower and the world's third pole, the QTP is geographically situated between 73°19~104°47′ east longitude and 26°00′~39°47′ north latitude, with a total area of about 2.61 million square kilometers (Figure 1). Its jurisdiction encompasses 182 counties within six provincial regions of China, including Tibet Autonomous Region, Qinghai Province, Xinjiang Uygur Autonomous Region, Gansu Province, Sichuan Province, and Yunnan Province (Meng et al., 2023). Elevation on the QTP predominantly ranges between 3000 m and 5000 m, with an average altitude exceeding 4000 m. With grasslands constituting over half of its land cover, the QTP emerges as one of the most important pastoral areas in China. Alpine steppe, alpine meadow, and temperate steppe characterize the main grassland types on the QTP (Han et al., 2019; Zhai et al., 2022; Zhu et al., 2023). The complex geographical and climatic conditions of the QTP contributes to the markedly heterogeneous grassland distribution, which correspondingly lead to the high heterogeneity in livestock distribution. Moreover, social and economic development, coupled with policy initiatives directed towards grassland restoration, have noticeably impacted the livestock numbers on the QTP over recent decades (Li et al., 2021).

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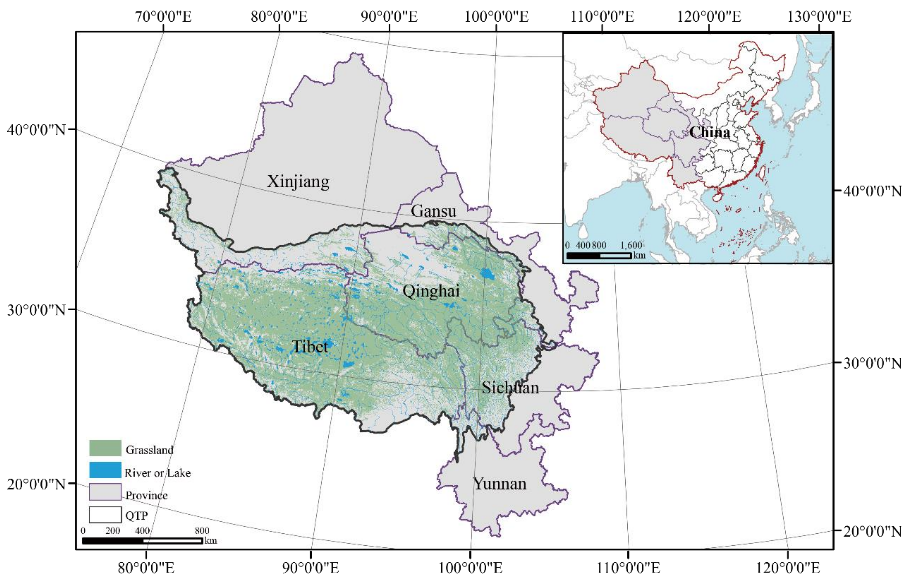

Figure 1. The geographic zoning map of the Qinghai-Tibet Plateau (QTP) superposed with grassland vegetation. Boundaries for the six provinces used for statistical analysis are also shown.

2.2 Data source

2.2.1 Census livestock data

The county-level census livestock data for the period between 1990 and 2020 were obtained from the Bureau of Statistics of each county across the QTP. The data includes the number of cattle, sheep, horse and mule, with the exception of counties in Yunnan Province, which lack data for the years from 1990 to 2007, and Ganzi Prefecture in Sichuan Province, which lack data for the years from 1990 to 1999, and Muli county in Sichuan Province, which lack data for the years from 1990 to 2007. In total, livestock data were available for 182 counties, and 4998 independent records were finally generated. Furthermore, the respective quantities of different livestock types are converted to Standard Sheep Units (SU), in compliance with the Chinese national regulations (Meng et al., 2023).

Due to the difficulty of collecting township-level census livestock data, the township data collected in this study only involved Baching County (2010-2018) and Gaize County (2018-2020) in Tibet, and Hongyuan County in Sichuan Province (2008). The township-level census livestock data cumulatively involves 18 townships with a total of 112 records, and were only used for auxiliary validation of the simulation results.

2.2.2 Factors affecting grazing activities

In this study, topography, climatic, environmental and socio-economic impacts were considered as influential factors on grazing activities (Li et al., 2021; Meng et al., 2023). Accordingly, altitude, slope, distance to water source, population density, air temperature, precipitation and human-induced impacts on NPP (HNPP) was selected as indicators. Specifically, elevation is derived from the DEM dataset accessible via the Resource and Environmental Data Cloud Platform of the Chinese Academy of Sciences (https://www.gscloud.cn), which also facilitated slope calculation. Rivers and lakes were obtained from the National Tibetan Plateau Data Center (https://data.tpdc.ac.cn), and the nearest Euclidean distance from each pixel to rivers or lakes is calculated accordingly. Meteorological elements such as daily air temperature and precipitation were downloaded from the China Meteorological Data Service Center (http://data.cma.cn). For the grid dataset that is not conditionally available, including population density, temperature, precipitation and HNPP, we detailed the creation process in the Supplementary file. All datasets utilized in this study were harmonized to consistent coordinate systems and resolutions (WGS 1984 Albers, 100 m).

2.3 Methodological framework

We developed a comprehensive methodological framework for mapping high-resolution grazing intensity on the QTP. Four major steps are included to predict the distribution pattern of grazing intensity: (1) identifying factors affecting grazing, (2) extracting theoretical suitable areas for livestock grazing, (3) building grazing spatialization model, and (4) filtering the model and correcting the grazing map. An exhaustive explanation of each step is provided in Figure 2.

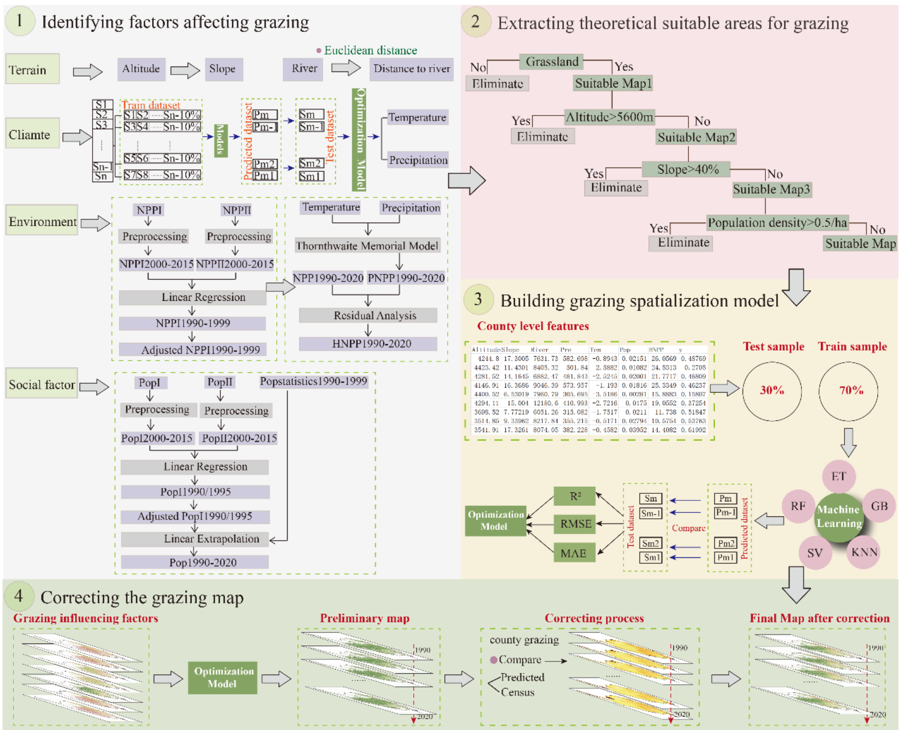

Figure 2. Flowchart of creating grazing intensity maps using different methods and source products.

2.3.1 Identifying factors affecting grazing activities

The spatial patterns of abiotic and biotic resources, incorporating food availability, environmental stress, and herder preference critically affect grazing activities (Meng et al., 2023). In light of this, seven influencing factors in four aspects were selected for grazing intensity mappingd (Figure 2-1).

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2.3.2 Extracting theoretical suitable areas for grazing

In this study, we assumed that grazing activities are confined solely to grassland. Consequently, the potential grazing areas were identified on the basis of grassland boundaries, which was extracted from the 30 m annual land cover dataset (CLCD) (Yang and Huang, 2021). Furthermore, grassland with slope over 40% and elevation higher than 5600 m respectively, were considered unsuitable for grazing and were therefore excluded from the potential grazing area in the subsequent simulations (Robinson et al., 2014; Meng et al., 2023). In addition, the grassland with population density greater than 50 inhabitants hm^{-2} were also excluded. The remaining isolated grassland was thus categorized as theoretical feasible grazing regions.

2.3.3 Building grazing spatialization model

By performing regional statistics, the annual average values for each grazing influence factor were extracted from the theoretically suitable grazing areas at the county scale, and were further used as independent variables in the model construction. The dependent variable for the model was acquired by determining the livestock density within each county, followed by a logarithmic transformation of the values to normalize the distribution of the dependent variable. Consequently, a total of 4998 samples were derived from the aforementioned independent and dependent variables. Of these samples, 70% were allocated for model training, while the remaining 30% comprised the test sets, serving to validate the model's performance. Subsequently, we built grazing spatialization models using five machine learning algorithms at the county scale, including Support Vector regression (SV) (Cortes and Vapnik, 1995; Lin et al., 2022), K-Nearest Neighbors (KNN) (Cover and Hart, 1967), Gradient Boosting regression (GB) (Friedman, 2001; Pan et al., 2019), Random Forest (RF) (Breiman, 2001) and Extra Trees regression (ET) (Geurts et al., 2006; Ahmad et al., 2018). Lastly, to assess the accuracy of the spatialized livestock map, the predicted livestock intensity values were juxtaposed with the livestock statistical data from each respective county.

2.3.4 Correcting the grazing map

We further used the optimal model to predict the geographical distribution of grazing density across the QTP. To maintain better consistency between the predicted livestock number and the census data, the estimated results were adjusted using the census livestock numbers at the county scale as a control. Consequently, the corrected and refined map is presented as the final grazing intensity map in this study.

2.4 Accuracy evaluation

We used three accuracy validation indexes to evaluate the performance of five machine learning algorithms, including coefficients of determination (R^2), mean absolute error (MAE), and root mean square error (RMSE), by through a comparison of the predicted value with the census data. The definitions of three metrics are presented in Eq. (1)~(3).

$$R^2=1-\frac{\sum_{i=1}^{n}(C_i-P_i)^2}{\sum_{i=1}^{n}(C_i-\overline{C})^2} \quad (1)$$

$$\mathrm{MAE}=\frac{1}{n}\sum_{i=1}^{n}|C_i-P_i| \quad (2)$$

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$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(C_i\text{-}P_i)^2} \quad (3)$$

where C_i and P_i are the census livestock data and the predicted value for county i, respectively; $\overline{C}$ represents the mean census value for all county; and n gives the total number of counties.

3 Results

3.1 Performances of models

Table 1 summarizes the efficiency of the five used machine learning models with considering all three accuracy evaluators of R^2, MAE and RMSE. It can be seen that the ET model performs the best, with its R^2 exceeding 0.955, and MAE (0.081 SU/hm^2) and RMSE (0.164 SU/hm^2) significantly lower than the value of RF, GB, KNN and SVM models. Figure 3 illustrates the correlation between the census livestock data and the livestock numbers predicted by the model for each county from 1990 to 2020. It demonstrated that the ET-predicted data displayed a distribution pattern consistent with that of other models, but the scatter points of the ET model were more convergent to the 1:1 diagonal line, indicating a superior fit compared to the other models. These comparisons suggest that the ET model possesses superior robustness and can, therefore, provide stable estimations of livestock intensity on the QTP.

Table 1. Comparison of mapping accuracy for five machine learning models based on the same validation datasets

Models	R^2	MAE (SU/hm^2)	RMSE (SU/hm^2)
ET	0.955	0.081	0.164
RF	0.928	0.099	0.208
GB	0.859	0.197	0.300
KNN	0.786	0.186	0.384
SVM	0.380	0.419	0.750

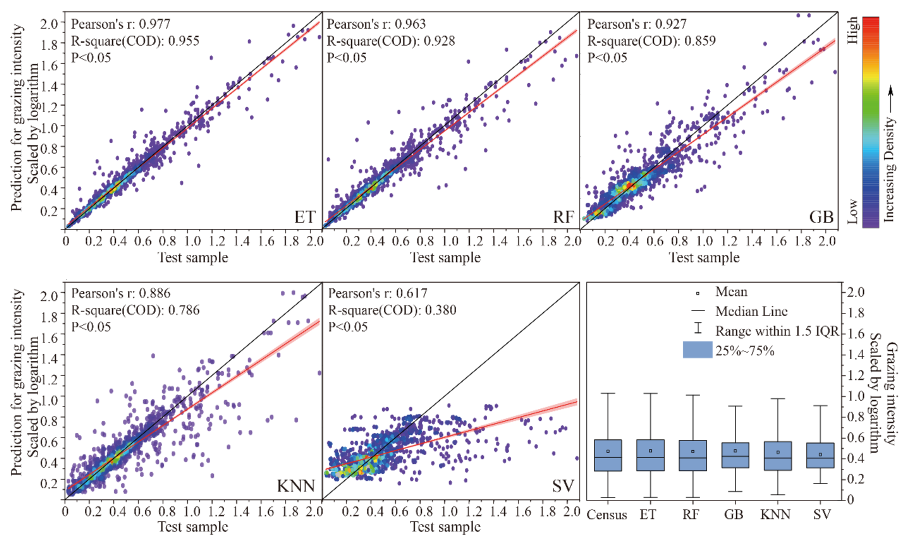

Figure 3. Scatterplots of model-predicted livestock numbers and census grazing data at the county scale. The red solid line and the black solid line are the fitting line and the 1:1 diagonal line, respectively.

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Utilizing the ET model, we predicted the spatio-temporal distribution of grazing intensity across the QTP from 1990 to 2020 with a resolution of 100 m × 100 m. To test the accuracy of these maps, we aggregated the prediction results from the pixel level to county level and compared them with the livestock census data (Figure 4a). It is evident that the predicted livestock intensity was highly consistent with the county-level census data, displaying particular robustness in lower grazing intensity scenarios (Figure 4b). Specifically, comparing with 2.983 SU/hm^2 for the mean census data, our county-level predicted datasets revealed an average grazing intensity of 3.106 SU/hm^2, with data discrepancies for 76.31% (number of counties=3814) not exceeding 0.6 SU/hm^2, and 91.74% (number of counties=4585) remaining under 1.0 SU/hm^2. Furthermore, employing county-level livestock census data as a benchmark for quality control, we obtained the final annual gridded datasets for grazing intensity (GDGI) across the QTP spanning 31 years from 1990 to 2020.

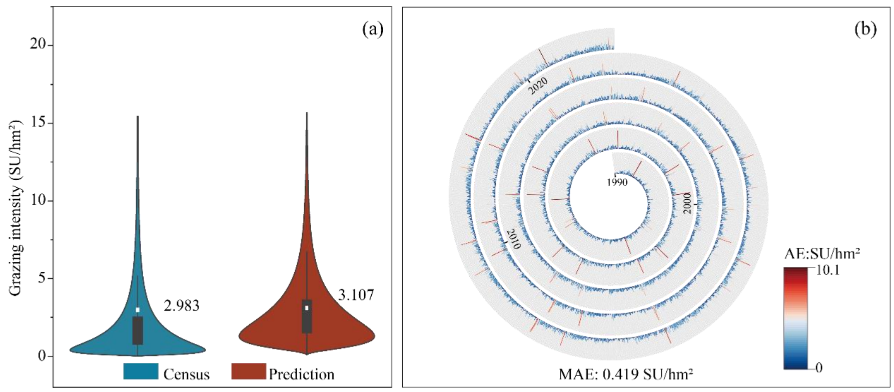

Figure 4. Accuracy of the ET-predicted grazing intensity results at spatial resolution of 100 m from 1990 to 2020. (a) comparison of the predicted value and the census data at the county scale; (b) absolute error for each county.

3.2 Validation of the GDGI dataset at the county scale

Figure 5a-c illustrated the highly consistency between the GDGI dataset and the county-scale census livestock data, as evidenced by R^2 of 1, and MAE and RMSE of 0.006 SU/hm^2 and 0.099 SU/hm^2, respectively. Moreover, the spatial heterogeneity within the counties was effectively reflected by the GDGI dataset, a characteristic not illustrated by the census dataset (Figure 5b, 5c). In terms of the temporal trends of grazing intensity, the GDGI dataset overall exhibited consistent trends with the livestock statistic data (Figure 5d-5f). Specifically, the census data indicated a substantial decline in grazing intensity from 1990 to 2001, followed by a period of fluctuation post-2001, which was successfully captured by the GDGI dataset (Figure 5). In addition, the GDGI dataset can also capture the spatial distribution of livestock, depicting a decrease and fluctuation in grazing intensity within western and certain central regions, whilst noting an increase in other areas (Figure 5e, 5f).

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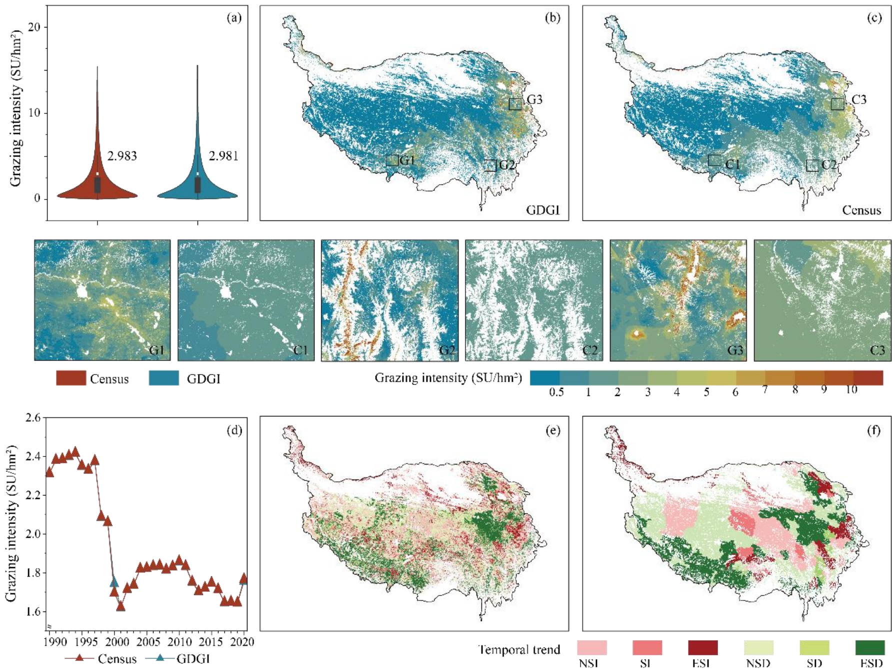

Figure 5. Validation of the GDGI maps using the census grazing data from 1990 to 2020: (a) violin plot of the census data and the predicted value; (b-c) spatial distribution in SU per pixel; (d) temporal change in SU per year; (d-f) spatial distribution of SU changes tested by sen's slope and Mann-Kendall.

Note: ESI for Extremely Significant Increase (slope>0 & p<0.01); SI for Significant Increase (slope>0 & p<0.05); NSI for Non-significant increase (slope>0 & p>0.05); ESD for Extremely Significant Decrease (slope<0 & p<0.01); SD for Significant decrease (slope<0 & p<0.05); NSD for Non-significant decrease (slope<0 & p>0.05).

Table 2. Accuracy assessments for the GDGI dataset in different provinces from 1990 to 2020

Province	Number of counties	Census (SU/hm^2)	GDGI (SU/hm^2)	MAE (SU/hm^2)	RMSE (SU/hm^2)	R^2
XinJiang	13	3.231	3.246	0.017	0.230	0.997
YunNan	6	20.401	20.401	0.00	0.00	1
GanSu	14	7.459	7.439	0.020	0.143	1
QingHai	43	3.761	3.757	0.005	0.042	1
SiChuan	32	2.379	2.383	0.004	0.094	0.992
Tibet	74	1.225	1.223	0.010	0.025	0.993
QTP	182	2.983	2.981	0.006	0.099	1

Note: AE represents absolute error

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A further comparison of the accuracy of grazing intensity maps across various provinces revealed distinct differences. Specifically, Table 2 showed that Yunan province achieved the best accurate prediction (MAE=0.000, RMSE=0.00 and R^2=1), closely followed by Sichuan Province (MAE=0.004, RMSE=0.094 and R^2=0.992). Conversely, prediction performance from Xinjiang Uygur Autonomous Region trailed behind (MAE=0.017, RMSE=0.230 and R^2=0.997).

3.3 Validation of the GDGI dataset at the township scale

We further validated the precision of the GDGI dataset using the township-level livestock statistic data. Encouragingly, the evaluation results showed that the GDGI dataset still has excellent performance at the township scale (Figure 6a), with R^2 of 0.867, MAE of 0.208 SU/hm^2, and RMSE of 0.276 SU/hm^2. In addition, similarly to the census data, the GDGI dataset indicated that some townships with few grassland area are still under high grazing pressure (Figure 6b, 6c).

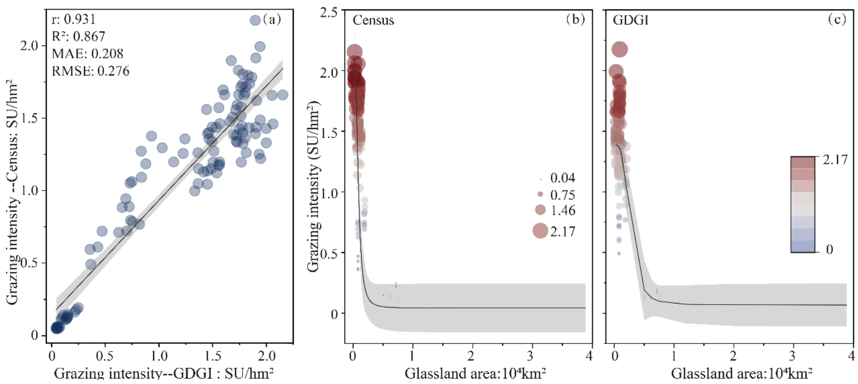

Figure 6. Validation results of grazing intensity between the GDGI dataset and the township census livestock data: (a) linear fit of predicted number and statistic data; (b-c) logistic fit of grazing data and grassland area.

4 Discussion

4.1 Comparison with other grazing intensity maps

To further assess the effectiveness and reliability of the developed GDGI dataset, the mapping results were juxtaposed with seven publicly available grazing intensity maps covering the QTP (Table 3). It can be seen that despite their public availability, these maps lacked both in spatial and temporal resolution when juxtaposed with the GDGI maps. Our analysis was extended to four openly accessible gridded livestock datasets, including GI-Sun (Sun et al., 2021), ALCC (Liu, 2021), GI-Meng (Meng et al. 2023) and GLWs (Gilbert et al., 2018). Among the GLW series, GLW3 and GLW4 were chosen owing to their superior performances over GLW1 and GLW2, as indicated by Gilbert et al. (2018). A commonality among all five maps was the consistency for the spatial patterns of grazing intensity, with prevalent high and low intensities in the northeast and northwest regions, respectively (Figure 7). However, these maps differed significantly in terms of accuracy. As the grazing intensity maps of GLWs and ALCC were produced based on the livestock census data in 2001 and 2015, an accuracy comparison for the corresponding years was conducted among the five datasets. It was observed from

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the scatter diagrams that R^2 between the predicted and livestock statistic data for GI-Sun, ALCC, and GLWs are lower than 0.6, which is significantly lower than the accuracy of GDGI (R^2 exceeds 0.9) (Figure 7a). Furthermore, GDGI exhibited the closest to the census data, as evidenced by the fact that MAE and RMSE are less than 1 (Figure 7b, 7c). Moreover, the GDGI dataset spanning 31 years (1990-2020) earmarked it as a more suitable choice for long-term studies in comparison to the other four datasets. Regarding spatial distribution, the overall patterns of these grazing maps are largely consistent, exhibiting higher density patterns in the southeast and lower in the northwest. However, notable discrepancies are still apparent in the finer details. Generally speaking, in terms of visually representing the spatial distribution of livestock, the GDGI maps exhibit the best performance.

The above advantageous of the GDGI dataset are understandable. First, the livestock census data used in GDGI is more detailed, aiding in enhancing the accuracy of the estimation results. Specifically, GI-sun, ALCC, GI-Meng and GDGI all use county-level livestock statistics to map grazing intensity, whereas GLW3 and GLW4 are based on provincial-level census data to map, which results in their accuracy lagging significantly behind the four other datasets (Nicolas et al. 2016, Sun et al. 2021). Second, grazing densities are estimated by dividing the number of livestock from the statistical data, after a mask excluding theoretical unsuitable grazing areas. However, these maps differ in their definitions of suitable grazing areas. In this study, as with the GI-sun and GI-Meng maps, we considered grazing to occur only on grasslands, and further excluded unsuitable areas such as high elevations and steep slopes. This kind of definition is clearly more reasonable than the GLW series, which removed only water bodies, urban core areas, and protected areas with relatively tight regulations of human activity (McSherry and Ritchie 2013, He et al. 2022). However, the GI-Meng dataset considers the core areas of protected areas as grazing-free region, it does not match the actual situation on the QTP (Zhao et al., 2020; Li et al., 2022b; Jiang et al., 2023). Those different thresholds for the definition of suitable grazing areas are account for the fact each map has different theoretical grazing regions. Third, these maps decompose the livestock census data to pixels based on different mathematical theories, which also leads to differences in prediction accuracy across maps. Specifically, ALCC used a multivariate linear regression algorithm to predict grazing intensity, which has been shown to be significantly inferior to the RF machine learning method employed by GI-Meng, GLW3 and GLW4 (Nicolas et al. 2016, Li et al. 2021). In this study, we used the ET model to predict livestock numbers and achieved higher accuracy accordingly. Finally, differences in the selection of factors affecting livestock distribution across maps may also lead to differences in map accuracy. Specifically, GI-sun only used the NPP as indicator, but it is not simply linearly related to grazing intensity (Gilbert et al., 2018; Sun et al., 2021; Ma et al., 2022). ALCC considered the population density, NPP, and terrain as indicators, which are also incomplete considerations of the influencing factors. On the other hand, GLW series dataset considered 12 factors, such as NDVI, EVI, population distribution and elevation. GI-Meng dataset incorporated 14 factors including NDVI, soil PH, available nitrogen, available phosphorus, and available potassium. However, GLWs and GI-Meng ignored the decrease in the prediction accuracy due to redundancy among the factors. In this study, we selected factors related to grazing activities including terrain, climate, environment and social factor, and constructed a prediction model with seven factors including population density, elevation, climate, and HNPP. Unlike other livestock products, this study used HNPP for the first time to replace the commonly used NPP, or NDVI, or EVI as indicator, which has be proved to be more accurately expressed the relationship between livestock and grassland (Huang et al., 2022).

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Table 3. Summary of map-derived parameters for this study and other seven public gridded livestock datasets covering the QTP.

Dataset	Accessibility	Census	Temporal resolution	Spatial resolution	Period (years)	Method	Livestock type
GDGI	Yes	County	annual	100 m	1990-2020 (31)	ET	Standard SU
GLW3	Yes	Province/sub-Province	annual	0.083° (≈10 km)	2001 (1)	RF	Cattle, ducks, pigs, chickens,
GLW4	Yes	Province/sub-Province	annual	0.083° (≈10 km)	2015 (1)	RF	sheep, goats
GI-Sun	Yes	County	five-year interval	1 km	1990-2015 (6)	LRA	Standard SU
ALCC	Yes	Province/sub-Province	annual	250 m	2000-2019 (20)	MLR	Standard SU
GI-Meng	Yes	County	annual	0.083° (≈10 km)	1982-2015 (34)	RF	Standard SU
GI-Li	No	County	five-year interval	1 km	2000-2015 (4)	DNN	Cattle and sheep
GI-Zhan	No	County	season	15″ (≈500 m)	2020 (2)	RF	Standard SU

Note: LRA is the abbreviation of linear regression analysis.

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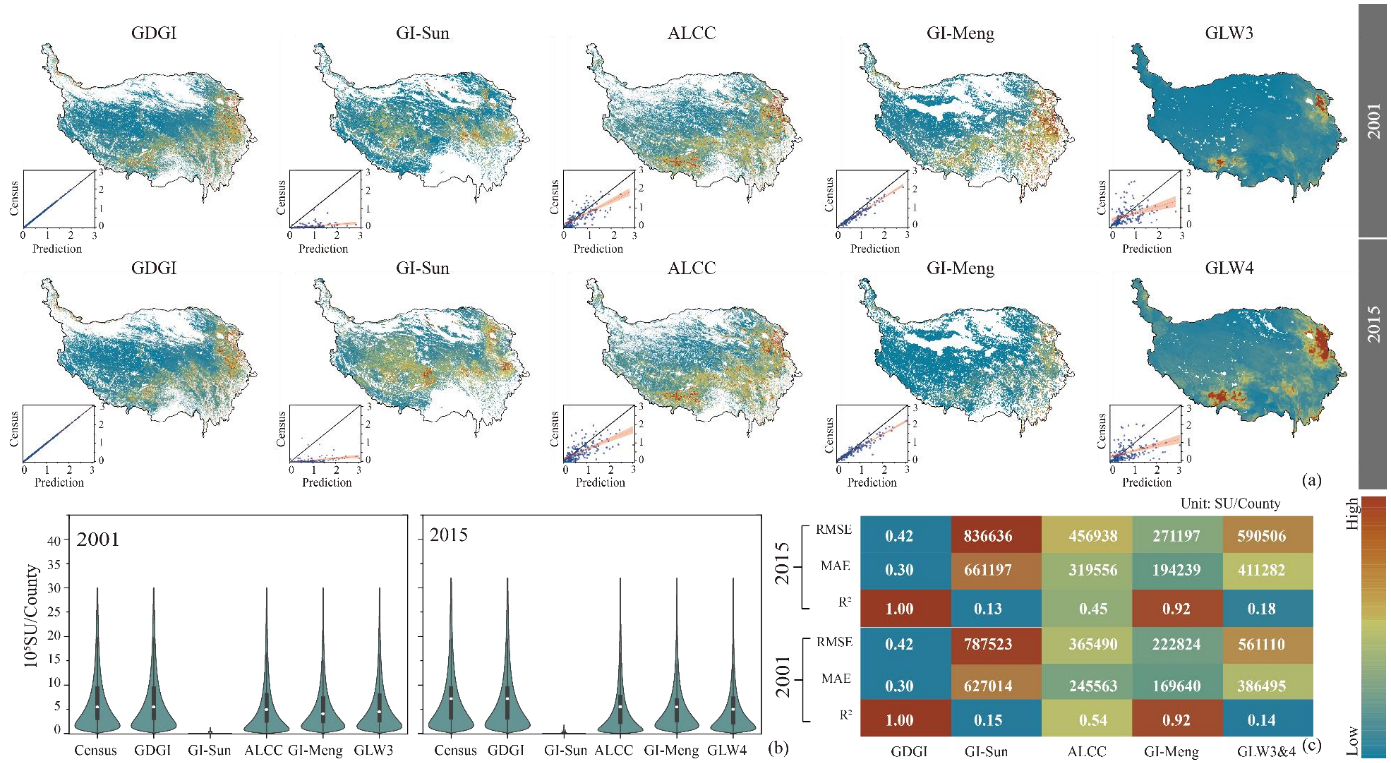

Figure 7. Comparisons of different grazing datasets for the years 2001 and 2015: (a) spatial patterns; (b) predicted livestock number and census data at county scale; (c) accuracy evaluation between predicted livestock number and statistic data.

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4.2 Implications for grazing management

Nearly half of the grasslands on the QTP have been reported to be degraded over the past four decades (Wang et al. 2018; Dong et al. 2020), with some reports even indicating that the degraded grassland has reached 90% (Wang et al. 2021). It is widely recognized that overgrazing is the predominant and most pervasive unsustainable human activity continuing to drive grassland degradation on the QTP (Wang et al. 2018; Chen et al. 2019). However, identifying overgrazed areas remains an important challenge that can be effectively addressed by grazing intensity maps.

According to the GDGI maps generated in this study, high-intensity grazing activities are mainly concentrated in the northeastern part of the QTP, with the grazing intensity in some areas even nearly more than ten times than the average value of the entire plateau (Figure 5b). Therefore, there is an urgent need to optimize grassland resource management in these areas. Encouragingly, the GDGI dataset show a decreasing trend in grazing intensity over the past 31 years in about two-thirds of the QTP. This trend is also consistent with other studies (Li et al. 2021, Sun et al. 2021). The areas with decreasing grazing intensity on the QTP are mainly located in the Sanjiangyuan region and the northern foothills of the Himalayas (Figure 5e).

The spatial heterogeneity of grazing intensities on the QTP may be attributed to the following reasons. First, complex geographic and climatic conditions on the QTP determine the heterogeneity of grassland, which in turn affects livestock distribution (Wang et al. 2018; Wei et al. 2022). Second, social-economic development is another important factor. In areas where social-economic development is relatively lagging behind, herders sought to increase livestock numbers in efforts to improve household incomes, leading to greater pressure on grasslands in these regions (Hammad and Tumeizi, 2012; Fang and Wu, 2022). In addition, the perceived increases in human population also resulted in the considerably increased need to more livestock numbers (Wei et al. 2022). Finally, the policy-induced reduction of livestock number might be one potential explanation for the grazing intensity decrease on the QTP. For example, Chinese government passed the Grassland Law in 1985, implemented the Grazing Withdrawal Program in 2003, approved the implementation of the Qinghai-Tibet Plateau Regional Ecological Construction and Environmental Protection Plan in 2011, and implemented the Law of the People's Republic of China on Ecological Protection of the Qinghai-Tibet Plateau in 2023. Moreover, environmental protection programs, including Grazing Withdraw Program (GWP), conversion of cropland to grassland, ecological compensation, fencing degrading grassland, and controlling the number of livestock have been implemented throughout the QTP since 2000. All these policies focused on applying grazing bans and can promote the sustainable use of grasslands, which resulted in the overall decrease of grazing intensity during the past three decades in the QTP.

4.3 Uncertainties and limitations

There are still some uncertainties and limitations in this study. First, we embarked on mapping grazing intensities, but these are fundamentally conservative estimations. For example, the livestock stocking numbers utilized were from year-end data at the county scale, inadvertently leading to a possible underestimation of grazing intensity due to our inability to consider livestock off-take rates within the constraints of data availability. Likewise, forage-dependent livestock were not considered in our study. Second, although seven main factors affecting livestock distribution were identified in this

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study, we still did not fully cover all influential factors. For instance, factors like fencing, road proximity, and grazing season transformation were not taken into account in this study, which potentially influencing the livestock distribution. Third, some baseline data also need to be improved. For example, the gridded 100-m population density data during the 1990-1999 period were absent. Although we supplemented this data by using linear extrapolation method, errors arising from the resampling process may have propagated further uncertainties. Fourth, the ET model in this study was trained with only 4998 samples and subsequently applied to a massive 150 million pixels, possibly compromising the accuracy of model simulations due to the lack of training samples. Last, we assessed merely the livestock grazing intensity, excluding wild herbivores, thereby potentially underestimating the actual grazing pressure on the QTP. We henceforth recommend that subsequent efforts should explore the inclusion of more detailed livestock census data, more appropriate factors, and strive for refinement in the time series persistence of key datasets.

5 Data availability

The annual gridded grazing intensity maps of the QTP spanning from 1990 to 2020 are accessible at the following link: https://figshare.com/s/ad2bbc7117a56d4fd88d (Zhou et al., 2023). Each map is catalogued by year and recorded in GeoTIFF format, with values represented in SU/hm^2 per year. These datasets, with a spatial resolution of 100 m and annual temporal resolution, utilize the WGS-1984-Albers geographic coordinate system. To streamline data transfer and download processes, the comprehensive 31-year dataset has been compressed into a ZIP file, readily available for download and compatible with Geographic Information System (GIS) software for viewing.

7 Conclusions

In this study, we introduce a framework utilizing ET machine learning algorithms to achieve fine-scale livestock spatialization, subsequently generating the GDGI dataset across the QTP. The GDGI has a spatial resolution of 100 m and expands 31 years from 1990 to 2020. It is consistent with livestock census data, and can better highlight grazing intensity details, and has a relatively higher precision. The MAE for the QTP is 0.006 SU/hm^2 based on 4998 independent test samples. In addition, the accuracy evaluations at both county-level and township-level underscore the outstanding reliability and applicability of the GDGI dataset, which can successfully capture the spatial heterogeneity and variation in grazing intensities in greater details. Moreover, comparisons between the GDGI dataset and other existing grazing map products further proved the robust and efficient of our dataset, and demonstrate the validity of the proposed framework in the research of livestock spatialization. The GDGI dataset presented in this study can address existing limitations and enhance the understanding of grazing activities on the QTP. This, in turn, can aid in the rational utilization of grasslands and facilitate the implementation of informed and sustainable management practices.

Supplement.

For gridded datasets influencing grazing that are not directly available, or that do not meet spatio-temporal resolution requirements—such as those pertaining to population density, temperature, precipitation, and HNPP—we have delineated the processing or creation procedures in the Supplementary file.

Author contributions.

TL conceived the research; JZ and JN performed the analyses and wrote the first draft of the paper; NW and TL reviewed and edited the paper before submission. All authors made substantial contributions to the discussion of content.

Competing interests.

The authors declare that they have no conflict of interest.

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